Term : Fall
Year : 2023

PHIL7001: Fundamentals of AI, Data and Algorithms

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Course Description

This course will be a general introduction to the fundamental data science tools and techniques used in modern machine learning and artificial intelligence systems. We will aim to understand the central building blocks required for critical analysis and assessment of the legal, ethical and political issues brought about by the introduction of algorithmic decision making in business, law, and government.

In Part I, we will study data, probability, and statistics. We will introduce core notions of probability spaces, random variables, and distributions. We will also study univariate inferential methods, including the Bayesian approach. Finally, we will study relationships between random quantities, focusing in particular on linear (regression) models. This is a crucial stepping stone between statistical inference and machine learning/AI.

In Part II, we will study machine learning and AI. We start with linear (regression) approaches to classification. We then look at certain influential and intuitive non-linear methods (decision trees, random forests, and support vector machines). Then we will study neural networks, deep learning and reinforcement learning. Finally, we will study natural language processing and large language models.

There will be several case studies throughout the class. The case studies present issues that commonly arise when machine learning and AI are introduced into corporate finance, criminal justice, and health care. During the case studies, you will work in small groups to solve several problems, which we will later debrief in class.

Materials

I will post all required readings to the course webpage. No textbook is required but we will draw from the sources below.

Ross, Introduction to Probability Models (2021).
Faraway, Linear Models with R (2005).
Gelman et al, Bayesian Data Analysis, 3d Ed (2021).
Wickham and Grolemund, R For Data Science (2023).
Goodfellow et al, Deep Learning (MIT Press, 2016)
Sutton and Barto, Reinforcement Learning: An Introduction (MIT Press, 2018)
Justin Bois, Distribution Explorer (https://distribution-explorer.github.io/)

Assignments

Grades will be based on the following:

Midterm: 40%
Final: 40%
Participation and case studies: 10%
Homework: 10%

The midterm and final exams will be in-class. You will have 3 hours to complete each test. The test will be closed book, but you can bring one "cheat sheet" (instructions will be provided in class). You can use a basic (non-graphing) calculator, but no smart devices of any kind are permitted.

Participation and case study grades will be calculated on the basis of class attendance, group participation, case study completion, and in-class contributions. This is a large class, and we will keep in mind that in class contribution may be limited. However, there will still be opportunity to engage.

For example: I may call on students to answer a question, or address a reading, and when called on, students will be expected to provide a meaningful/insightful answer. This does not mean I will reward those who "talk the most" or punish those who "talk the least". You are simply required to attend, be attentive, be present, and contribute meaningfully.

Please come to class on time, we will start promptly and avoid interruptions.

Homework assignments will be short, and are designed to test your understanding of the material as preparation for the exam. There will be two homework assignments.

Prerequisites

While there are no hard prerequisites, the course covers quite a bit of formal material, and if you have no background in probability and statistics, you should plan ahead and speak to me if necessary.

Part I: Data, Probability and Statistics

Week 1: Introduction

Lecture 1. Risk and Uncertainty: Subways, Coconuts and Black Swans
Reading
Makridakis, Hogarth and Gaba, Why Forecasts Fail (MIT Sloan Review, 2010).

Lecture 2. Fundamentals of Probability and Bayes' Rule
Reading
Ross, Chapter 1.

Week 2: Statistical Computing

Lecture 3: Introduction to R and RStudio
Reading
Wickham and Grolemund, Chapter 1 (to be used as reference)
Haschke, An Introduction to R (2013) (to be used as reference).

Lecture 4: R and RStudio Practice Session
Reading
Wickham and Grolemund, Chapter 3, sections 3.1-3.3 only.

Week 3: Probability Spaces

Lecture 5: Probability Spaces and Distributions
Reading
Ross, Chapter 2, 2.1 (pgs. 21-25), 2.2.1 (pgs. 26-27), 2.2.2 (pgs. 27-29), 2.3.1 (pgs. 32-34), and 2.3.4 (pgs. 34-36).

Lecture 6: **Case Study 1**: Monty Hall Meets AI
Reading
Tierney, Behind Monty Hall's Doors: Puzzle, Debate and Answer (New York Times, 1991).

Week 4: Statistics

Lecture 7: Decisions, Estimation and Hypothesis Tests
Goodman, The P-Value Fallacy (Annals of Internal Medicine, 1999).

Lecture 8: Bayesian Inference
Reading
Lindley, Inference for a Bernoulli Process (A Bayesian View), (The American Statistician, 1976).

Week 5: Linear Models

Lecture 9: Fundamentals of Regression

Lecture 10: **Case Study 2**: Gender Discrimination in Venture Capital
Required
Hassan et al, How the VC Pitch Process is Failing Female Entrepreneurs (Harvard Business Review, 2020)

Week 6: Midterm Exam

Part II: Machine learning and AI

Week 7: Linear Learning

Lecture 13: Fundamentals of Classification

Lecture 14: Logistic Regression
Reading
Stanford Open Policing Tutorial, https://openpolicing.stanford.edu/tutorials/

Week 8: Non Linear Learning

Lecture 15: Random Forests and Support Vector Machines

Lecture 16: **Case Study 3**: Criminal Justice and Recidivism Prediction
Reading
Angwin et al, Machine Bias, Pro Publica (2016).

Week 9: Deep Learning

Lecture 17: Introduction to Neural Networks and Deep Learning

Reading
Goodfellow et al., Deep Learning (MIT Press, 2016), Ch. 6 (to be used as reference)

Lecture 18: Deep Learning

Week 10: Multimodal Learning

Lecture 19: Reinforcement Learning
Reading
Sutton and Barto, Reinforcement Learning: An Introduction (MIT Press, 2018), Ch. 1 (to be used as reference)

Lecture 20: Natural Language Processing

Week 11: Foundation Models and Generative AI

Lecture 21: Introduction to Large Language Models
Reading
Jay Alammar, The Illustrated Transformer, https://jalammar.github.io/illustrated-transformer/

Lecture 22: Case Study 4: ChatGPT, Task Rabbit, Lies, and Other Attitudes
Reading
GPT-4 Technical Report (Open AI, 2023) (excerpts only)

Week 12: Final Exam

Submitting Assignments and Late Policy

Submittable work must be submitted online by 11:59pm on the day it is due, unless otherwise instructed.

If you anticipate needing more time on an assignment, you should ask me in advance. Otherwise, late assignments will be penalized by one-fourth of a letter grade for each day they are late.

Students with Disabilities

If you think you may need accommodation for a disability, please contact me or campus accessibility services as soon as possible.

Plagiarism

Written work submitted for a grade in this course must be your own. You are responsible for making sure that none of your work is plagiarized. Cite the sources you rely on, and err on the side of caution where necessary.